USING SMARTPHONE DETECTING REAL TIME COUGH EVENTS BY FUZZY CLASSIFIER ALGORITHM

[1]NANCY.P, [2]LEO SAHAYA DHARSHINI.A & [3]SRI THATCHAYANI.G
[1]*Assistant Professor,* [2]*Assistant Professor,* [3]*Assistant Professor*
[1]*Biomedical Department,* [2]*Biomedical Department,* [3]*Biotechnology Department*
[1]*Sri Shakthi Institute of Engineering and Technology, Coimbatore, Tamilnadu, India.*
[2]*RVS Educational Trust's And Group of Institution, Dindigul, Tamilnadu, India.*
[3]*Sri Shakthi Institute of Engineering and Technology, Coimbatore, Tamilnadu, India.*
[1]*nanupete@gmail.com,* [2]*leo.dharshini@gmail.com,*[3]*srithatchayani@siet.ac.in*

Abstract: *The efficiency of telemedicine in respiratory health care has not been completely unveiled in part due to the inexistence of reliable objective measurements of symptoms such as cough. Automatic cough detection is an established field of research with a number of systems achieving high sensitivity and specificity. Currently available cough detectors are uncomfortable and expensive at a time when generic smart phones can perform this task. Most systems in the literature rely on pattern recognition engines based on features extracted from cough sounds and other biomedical signals (chest movements, electrocardiograms, etc.), with the latter acting as support for the microphone signal. However, two major challenges preclude smart phone-based cough detectors from effective deployment namely, the need to deal with noisy environments and computational cost. This paper focuses on the latter, since complex machine learning algorithms are too slow for real-time use and kill the battery in a few hours unless specific actions are taken. In this paper, we propose a keyword-spotting approach, based on HMMs, to detect cough events from continuous ambulatory recordings from patients with different respiratory conditions. The idea in keyword- spotting is to detect occurrences of keywords in a continuous speech recording. In HMM-based keyword-spotting, only the patterns representing the keywords in which we are interested are modeled by specific models, while more general models, usually called ―filler models, are used to represent the rest of the data. In our implementation, we are interested in detecting ―cough sounds from continuous data, and we create statistical models to represent these patterns and detect their occurrence from the output of a recognizer*

Keywords: Cough Detection, HMMs, Keyword-spotting, Efficient Implementation, Fuzzy Classifier.

1. INTRODUCTION

Cough is a normal protective reflex which clears the respiratory tract and prevents the entrance of noxious materials into the respiratory system [1]. Cough is not frequent in healthy subjects, but it is a common symptom of many respiratory diseases, including asthma, gastro-oesophageal reflux (GOR) [2,3,4], postnasal drip, bronchiectasis and chronic bronchitis. A reliable measure of cough is needed so that the severity of cough in a particular patient and the effectiveness of treatment can be assessed. This evaluation of cough severity has so far relied mainly on subjective measures, such as cough reflex sensitivity, and on the patient's perception of the symptom, assessed by cough visual analogue scores[5], quality of life questionnaires, cough symptom scores and patient's diaries[6,7] . The subjectivity and lack of robustness of these tests have led to increased interest in developing automated ambulatory cough monitors as an objective method of measuring the frequency and intensity of cough in patients suffering from chronic cough, which could be used as a measure of cough severity [8,9]. The basic requirements for an automatic cough monitor are the possibility to record over a representative amount of time using a portable recording system[10,11,12] and the capacity to automatically detect the occurrences of cough sounds from the recordings using a specially designed algorithm[13,14]. Some systems have been proposed for ambulatory cough monitoring [15,16], allowing up to 24 h of recording, but they still rely on human experts to manually analyze the recordings and select the occurrences of cough sounds[17] .

We previously demonstrated that pairing Hu moments and a standard fuzzy classifier achieved accurate cough detection at the expense of computation time [18,19]. To speed-up fuzzy search, many tree structures have been proposed. Our cough detector uses an improved vp-tree with optimized construction methods and a distance function that results in faster searches [20,21]. We achieve 18x speed-up over classic vp-trees, and 560x over standard implementations of fuzzy in state-of-the-art machine learning libraries, with classification accuracies over 93%, enabling real-time performance on low-end smart phones. In our implementation [22], we are interested in detecting ―cough‖ sounds from continuous data, and we create statistical models to represent these patterns and detect their occurrence from the output of a recognizer.

2. EXISITNG SYSTEM

The existing system has no provision to authenticate the user of wireless systems. Has no automatic messaging during emergency situations has no provision for multi system interfacing. k-NN (k Nearest Neighbor) is a algorithm used here, algorithm is a set of procedure which follow the steps. In this system they proposed the peripheral integrated circuit (PIC) microcontroller, it is very efficence, but it need a peripheral integrated circuit, so we modified the project with Arduino UNO.

They used the k-NN algorithm that stores all available cases and classifies new cases based on a similarity measure.KNN has been used in statistical estimation and pattern recognition already in the beginning of 1970’s as a non parametric technique.

3. PROPOSED SYSTEM

These potential of telemedicine in respiratory health care has not been completely unveiled in part due to the inexistence of reliable objective measurements of symptoms such as cough .Currently available cough detectors are uncomfortable and expensive at a time when generic smart phones can perform this task. However, two major challenges preclude Smartphone-based cough detectors from effective deployment namely, the need to deal with noisy environments and computational cost. This project focuses on the latter, since complex machine learning algorithms are too slow for real-time use and kill the battery in a few hours unless specific actions are taken

BLOCK DIAGRAM

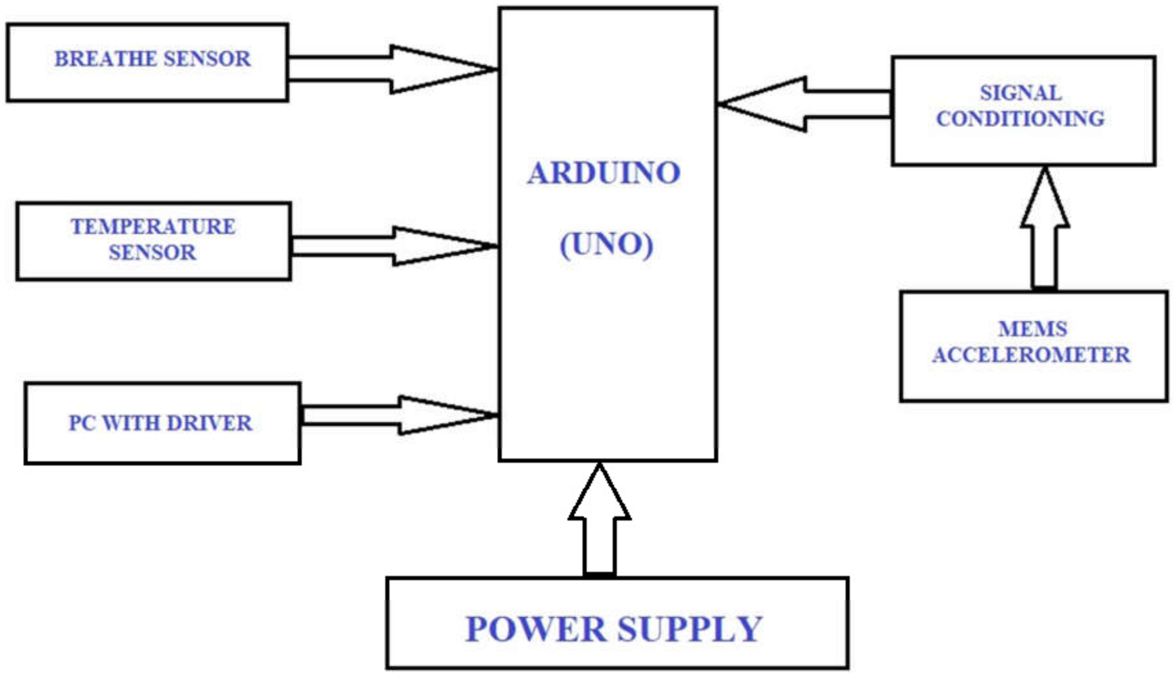

Figure 1. Block Diagram

4. RESPIRATION SENSOR

4.1. RESPIRATION RATE MEASUREMENT

The respiration rate is the number of breaths a person takes per minute. The rate is usually measured when a person is at rest and simply involves counting the number of breaths for one minute by counting how many times the chest rises. Respiration rates may increase with fever, illness, and with other medical conditions. When checking respiration, it is important to also note whether a person has any difficulty breathing. Normal respiration rates for an adult person at rest range from 12 to 16 breaths per minute. Digital Respiration Rate Meter uses a displacement transducer for sensing the respiration rate using IR transmitter and receiver as shown in the physical assembly. Inhaling and exhaling the air during respiration causes a light ball to move up and down in a capillary glass tube. This movement is sensed with the help of an IR transmitter- receiver assembly of the sensing circuit and converted into pulses through the pulse generator. These pulses are counted for a minute using a counter.

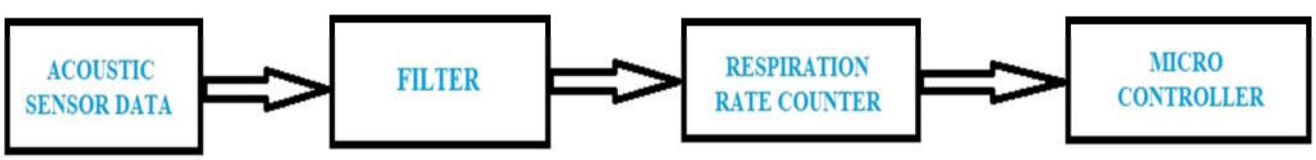

Figure 2. Respiration Rate Counter Diagram

Acoustic sensor data: In order to record the breaths of the subject, we use a standard microphone. The data collected from the recorded signal is used for further processing.

Filters: The data obtained from the original signal is the raw signal contaminated by a lot of external noise. In order to remove the noise and to smoothen the signal we use a low pass filter probably third order Butterworth filter. Due to filtering, unwanted noise in the raw signal is removed and good quality signal is obtained.

Respiration/Breathing rate counter: The breathing counter helps in detecting the number of breaths taken in one minute. This count is very important for the classification as it is based on number of breaths per minute.

5. TEMPERATURE SENSOR

5.1. LM34/LM35PRECISION MONOLITHIC TEMPERATURE SENSORS (INTRODUCTION)

Most commonly-used electrical temperature sensors are difficult to apply. For example, thermocouples have low output levels and require cold junction compensation. Thermistors are nonlinear. In addition, the outputs of these sensors are not linearly proportional to any temperature scale.

For purposes of discussion, suppose that a value of VPTAT equal to 1.59V will give a correct output of 770 mV at 77^0F.Then n will be equal to VPTAT/DVBE or 1.59V/60 mV e26.5, and VPTAT will have a temperature coefficient (temp- co)of:

$$\frac{\mathbf{nk}}{\mathbf{q}}\ln\frac{\mathbf{l_1}}{\mathbf{l_2}} = \mathbf{5.3\ mV/°C}$$

Subtracting two diode drops of 581 mV (at 77^0F) with tempcos of b2.35 mV/^{0}C each, will result in a voltage of 428 with a tempco of 10 mV/§C at the non- inverting input of amplifier A2. As shown, amplifier A2 has a gain of 1.8 which provides the necessary conversion to 770 mV at 77F (25C). A further example would be if the temperature were 32§F (0^0C), then the voltage at the input of A2 would be 428mV±(10 mV/§C) (25§C) e 0.178, which would give VOUT e(0.178) (1.8) e 320 mVÐthe correct value for this temperature.

6. SIGNAL PREPROCESSING

The audio signal from the device's microphone is sampled at 8.82 kHz, a frequency shown appropriate for cough event detection [25]. After that, 50ms windows with 25ms shift are extracted for classification using a Kaiser window with $\beta = 3.5$. As a starting point, the power spectral density (PSD) for each window is extracted and normalized. Initial speed-up is performed at this stage by using optimized FFT algorithms and taking advantage of the 25ms window overlap to perform only 50% of the required computations. A feature extraction block carries out the computation of local Hu moments as detailed in the Appendix to subsequently feed the pattern classification module where the efficient versions of the fuzzy algorithm have been implemented.

7. FEATURE EXTRACTION

In machine learning, pattern recognition and in image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature *selection*. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data.

8. FUZZY CLASSIFIER

8.1. FUZZY SET

A Fuzzy Set is any set that allows its members to have different grades of membership (membership function) in the interval [0,1].

8.2. FUZZY LOGIC

Fuzzy logic models, called fuzzy inference systems, consist of a number of conditional "if-then" rules. For the designer who understands the system, these rules are easy to write, and as many rules as necessary can be supplied to describe the system adequately (although typically only a moderate number of rules are needed).

8.3. FUZZY CLASSIFIER

“Any classifier that uses fuzzy sets or fuzzy logic in the course of its training or operation”, then the classifier is known as Fuzzy classifier.

A *classifier* is an algorithm that assigns a class label to an object, based on the object description. It is also said that the classifier *predicts* the class label. The object description comes in the form of a vector containing values of the features (attributes) deemed to be relevant for the classification task. Typically, the classifier learns to predict class labels using a training algorithm and a training data set. When a training data set is not available, a classifier can be designed from prior knowledge and expertise. Once trained, the classifier is ready for operation on unseen objects.

8.4. PRE PROCESSING

Testing and training of samples are done in this process. Samples are processed along a path from the root to a leaf in each tree by performing a binary test at each internal node along this path. The binary test compares a certain feature with a threshold. To identify the set of tests at each node and to separate the data into the different training classes.

Each training sample is sent to the corresponding child depending on the result of the test, and the process is recursively repeated until the number of samples in a node falls below a threshold, a predefined maximum tree depth is reached, or all the samples belong to the same class. In that case, the node becomes a leaf, and the most frequent class of the training data at the node is stored for testing.

8.5. TESTING

During testing, a new sample is processed by applying respective tests according to the path from the root node to the leaf it traverses. When a leaf node is reached, the tree casts a vote corresponding to the class assigned to this node in the training stage. The final decision for a test sample is obtained by selecting the class with the majority of votes. Moreover, the class probability of a test sample is estimated as the fraction of votes for that class cast by all trees.

In the proposed work, we propose a robust approach to hyper-spectral (HS) image resolution enhancement based on fuzzy logic. Using fuzzy approach,

i) Removing impulse noise,

ii) Smoothing out non-impulse noise, and

iii) Enhancing (or preserving) edges and certain other salient structures.

Image fuzzification, modification of membership values, and image defuzzification (if necessary). We encode image data (fuzzification) and decode the results (defuzzification) to process images by means of fuzzy techniques as follows:

- Define linguistic variable
- Develop membership function
- Develop Rules
- Fuzzy
- Defuzzy

8.6. ALGORITHM OF FUZZY APPROACH

Using fuzzy fusion approach, we will analyze the differences between each pixel using a local operator. Fuzzy approach is used when there is uncertainty and no mathematical relations are easily available. One of the major advantages of fuzzy logic over other existing fusion methods is that it permits the user to define the labels as rules.

9. RESULT AND DISCUSSION

- ✓ Graph cut algorithms are successfully applied to a wide range of problems in vision and graphics. Here we used this graph cut technique to solve the image segmentation problem. And we got successful results in partitioning an in image. In this project, we use the normalized cut technique to do the segmentation of an image.

- ✓ By linking the spatial neighbors as edges, the GC algorithm establishes a graph to describe the spatial interactions of hyper-spectral image pixels. This exactly corresponds to our start point of merging the spectral and the spatial information for hyper-spectral classification tasks. All the experiments have demonstrated the powerful abilities of the GC algorithm.

- ✓ Once the spanning forest is established, all the nodes are classified. In our GC algorithm, to establish the graph is only a preliminary stage by linking the adjacent pixels as edges. The max-flow/min-cut is the main processing.

- ✓ These benefits greatly occur in the integration of the spatial and the spectral information. Another advantage of our method is that, from the figures, the sharp corners of the objects can be seen clearly, benefiting from the idea of MRF with minimal spatial smoothing effect.

- ✓ The process of classification is done after the segmentation of an image into multiple parts. Hence, the new method has proven to be better than the previous approach.

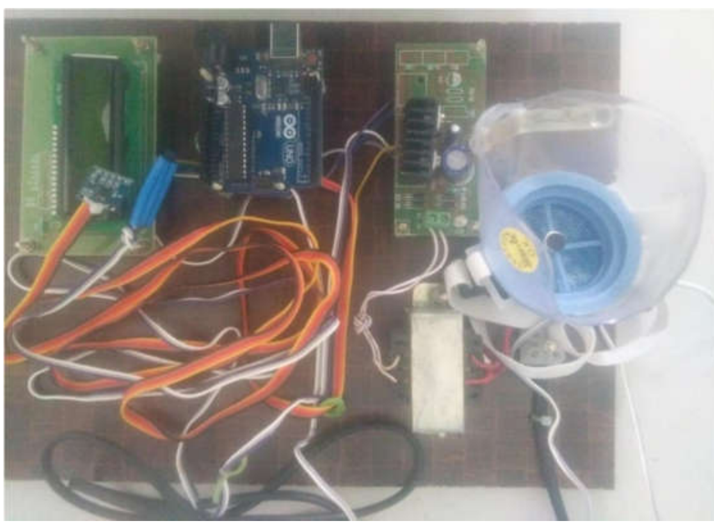

Figure 3.1 Our Model

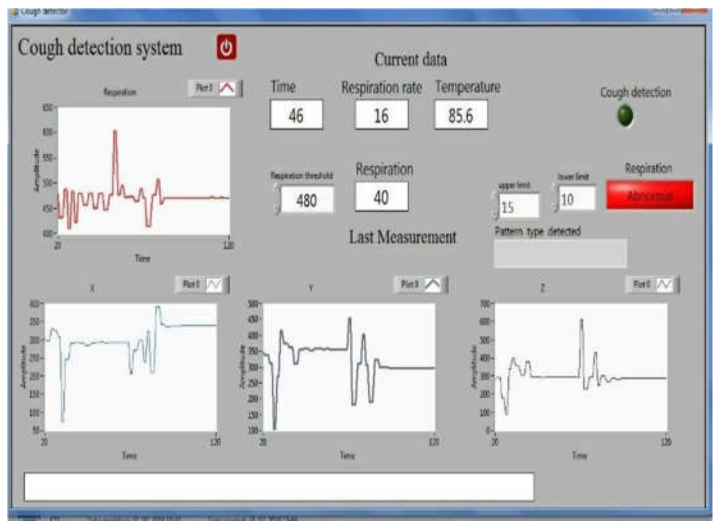

Figure 3.2 Output Image

10. CONCLUSION

This paper presents a robust and efficient implementation of a smartphone- based cough detector. Previous studies discarded the k-NN classifier as unacceptably slow and resource hungry for real-time processing in smartphones, while others had pointed out that the classification stage was the costliest part of the system, taking 31–44.9% of the CPU time, and being up to 8 times slower than the feature extraction module . The standard (non-optimized) Feature calculation of Hu Moments takes approximately 22ms per window when implemented on the smartphone used in our experiments. Adding the 51ms to classify each window with Weka's implementation prevented real-time detection, as new windows are generated every 25ms. We unveiled an interesting synergy between VP-trees and Euclidean2 distance that results in a fuzzy classifier that is fast and able to perform real-time detection on smartphones, without needing GPU acceleration or server off-loading. Our implementation classifies a new window in less than 1% of the CPU time spent computing the feature vector, performing the overall computation in less than 23ms. Our next goal will be to improve the efficiency of the rest of the modules of the system, to optimize database size, detect and correct false positives, and maximize the battery life of the device. To improve the accuracy in real life- scenarios, we plan to include a self-training module for personalized calibration. Such a module would increase the computation cost, as it involves updating the indexing tree. For efficiency reasons, it should not continuously run all the time, but rather would only be activated at user request for short-period sessions.

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